REAL-TIME ON-CHIP SEQUENTIAL ADAPTIVE PRINCIPAL COMPONENT ANALYSIS FOR DATA FEATURE EXTRACTION AND IMAGE COMPRESSION

Final Report

JPL Task 1042

Tuan A Duong, Bio-Inspired Technologies and Systems (3445)

A. OBJECTIVES

In recent years, the feature extraction approach [1] for data compression and object recognition has been drawing a lot of attention. Principal Component Analysis (PCA) [2-10] is one of the most effective linear techniques for feature extraction in the image-processing field. PCA is a statistical second-order analysis tool, and the principal information of the object can mostly be represented in a few principal component vectors. Based on a few principle components as features of the object, the recognition can be processed with less computational power and more reliability.

For object recognition in a dynamic environment, when the shape of the object keeps changing with time, real-time adaptive PCA can be an effective approach in dealing with this dynamical information and to keep track of the changes of its features. In order to enable the real-time adaptive PCA approach, the network is required to be simple, hardware-friendly and architecture-optimal so that the hardware implementation can be achieved.

The objective of this task is to study the feasibility of a real-time adaptive PCA approach which is applied to obtain real- time feature extraction for object recognition and data compression in the dynamic scene.

B. PROGRESS AND RESULTS

1. Science Data

It was found with the simulation that our proposed real-time adaptive PCA technique surpassed the current state of the art, e.g., gradient descent technique with respect to hardware simplification, fast learning convergence, and compact and low-power embodiment which enables real-time object recognition when implemented in VLSI hardware. The breakdown is shown below:

(1) Our *<u>DO</u>minant-element-based <u>G</u>radi<u>E</u>nt descent and <u>DYN</u>amic initial learning rate* (DOGEDYN) technique is compatible as a gradient descent technique in terms of identical convergent attractor, and in addition, our technique requires much less computation (one addition and multiplication per element) while the gradient descent technique requires n multiplications and n additions where n is the dimension of the input vector. This advantage will allow having less hardware, hence low power consumption and a compact engine (see appendix A).

(2) Our technique demonstrated its superiority in fast learning convergence as compared with the gradient descent technique (see appendix B) from which the real-time extraction may be achieved from the VLSI hardware approach.

2. Other Results

Due to the simplicity of our architecture and the less-computational requirement, the fully parallel hyperspectral extraction engine can be achieved on a single chip. The advantage of our technique is its capability to extract fully parallel spectral data for principal features in a high-speed, low-power and compact system.

C. SIGNIFICANCE OF RESULTS

This task developed a novel DODGEDYN technique for real-time adaptive PCA for feature extraction and data compression to solve the object-recognition problem in a dynamic environment.

The results indicated that the combination of two innovative techniques (dominant element component and initial dynamic learning rate) provided a faster-learning-convergence, less-computation, low-power and compact system. Hence, the real-time adaptive PCA engine can be achieved in VLSI hardware for object recognition or data compression in dynamic environment applications (e.g., real-time landing-site identification for NASA precision landing tasks).

D. FINANCIAL STATUS

The total funding for this task was $30,000 all of which has been expended.

E. PERSONNEL

Tuan A. Duong and Vu A. Duong

F. PUBLICATIONS AND PRESENTATIONS

[1] T.A. Duong, V. A. Duong, "A New Learning Technique Of Sequential Adaptive Principal Component Analysis For Fast Convergence and Simplified Hardware Implementation." In preparation for *IEEE. Trans. On. Neural Networks*.

[2] T.A. Duong "Real Time On-Chip Sequential Adaptive Principal Component Analysis for Data Feature Extraction and Image Compression", *GOMAC Tech-03, Vol. I*, pp. 460-464, Tampa, Florida, 31 March - 3 April, 2003.

[3] T.A. Duong and V.A. Duong, "Real-Time Principal Component Analysis Software For Feature Extraction And Data Compression", *NTR# 40046*, May. 03.

[4] T.A. Duong and V.A. Duong, “Real-Time On-Chip Principal Component Analysis Engine For Feature Extraction And Data Compression”, *NTR# 40034*, Feb. 03.

G. REFERENCES

[1] A.K. Jain, R.P.W. Duin, and J. Mao “Statistical Pattern Recognition: A Review”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, NO. 1, January 2000.

[2] R.O. Duda and P.E. Hart, Pattern Classification and Scene Analysis, New York, Wisley, 1973.

[3] P. Baldi and K. Hornik, “Learning in linear neural networks: A survey,” *IEEE Trans. Neural Networks*, Vol. 6, pp. 837-857, 1995.

[4] S. Haykin, *Neural Network-A Comprehensive Foundation.* New York: Macmillan, 1994.

[5] C. Chatterjee et. al. “Algorithms for accelerated convergence of adaptive PCA.” *IEEE Trans. Neural Networks*, Vol. 11, No. 2, pp. 338-355, March 2000.

[6] Y. Chauvin, “Principal component analysis by gradient descent on a constrained linear Hebbian cell,” in *Proc. Join Int. Conf. Neural Networks*, Vol. I, San Diego, CA pp. 373-380, 1989.

[7] Z. Fu and E.M. Dowling, “Conjugate gradient Eigenstructure tracking for adaptive spectral estimation,” *IEEE Trans. Signal Processing*, Vol. 43, pp. 1151-1160, 1995.

[8] E. Oja and J. Karhunen, “On stochastic approximation of the eigenvectors and eigenvalues of the expectation of a random matrix.” J. Math. Anal. Appl., vol. 106, pp. 69-84, 1985.

[9] T.D. Sanger, “Optimal unsupervised learning in a single-layer linear feedforward neural network,” *Neural Networks*, Vol.2 , pp. 459-473, 1989.

[10] L. Xu, “Least mean square error reconstruction principal for self-organizing neural-nets,” Neural Networks, 6, pp. 627-648, 1993.

H. APPENDICES:

A. CELL ARCHITECTURE

The energy function (objective function) is defined:

$$J_i(w_i) = \sum_{t=1}^{k} \left| y_i^t - w_i w_i^T y_i^t \right|^2 \tag{1}$$

And $$y_i^t = x_t - \sum_{j=1}^{i-1} w_j w_j^T x_t \tag{2}$$

$$w_{ij}^{new} = w_{ij}^{old} + \zeta_i \Delta w_{ij} = w_{ij}^{old} + \zeta_i \varepsilon_{ij} (w_i^T y_i^t + w_{ij} y_{ij}^t) \tag{3}$$

Where $\zeta_i = \dfrac{E_0}{E_{i-1}}$ and $\hat{y}_i^t = w_i w_i^T y_i^t$

Where k is the number of measurement vectors, x_t is a measured vector at time t and w_i is the i^{th} principal vector (or eigen vector).

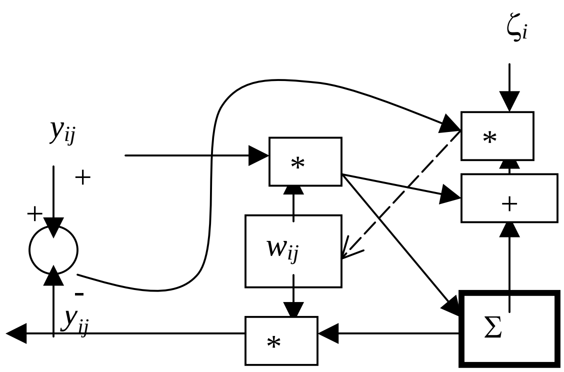
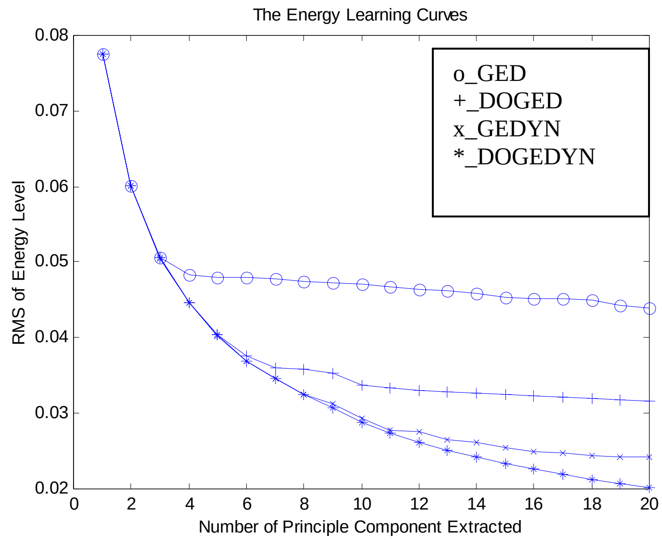


Figure 1: Single New PCA learning unit.

In Figure 1, the raw input data x_t is subtracted from the sum of the previous projected data on the previous principal components to obtain y_i^t as defined in the equation (2). The Σ box provides the inner product between vectors y_i^t and w_i. The result of the Σ box operation will, again, be summed with the previous multiplication of y_{ij}^t and w_{ij} and its output will be multiplied with the learning rate ζ_i before updating to w_{ij} as described in equation (3). This single unit can be cascaded into n units to obtain a PCA learning vector and this learning vector can be cascaded to obtain many components as parallel eigenvector extractors as needed for each application.

B. ENERGY LEARNING LEVEL VS PRINCIPAL COMPONENT EXTRACTED



The DOGEDYN, <u>G</u>radi<u>E</u>nt <u>D</u>escent (GED), <u>DO</u>minant element based <u>G</u>radi<u>E</u>nt <u>D</u>escent (DOGED), <u>G</u>radi<u>E</u>nt <u>D</u>escent with <u>DYN</u>amic initial learning rate (GEDYN) techniques are used in this study. In the Figure above, the DODGEDYN has shown its superiority in convergence in energy reduction (y-axis) for each component extracted (x-axis) with the fixed 150 batch iterations as compared with GED, DODGED, and GEDYN where the energy level is defined in equation (1). The GED technique is flat out at third component, the DOGED is up to sixth component, and the GEDYN is able to extract around eleventh component.